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A Novel Evaluation Method Based on Entropy for Image Segmentation

Xiaoling Chen[a], Riming Wang[a], Yunfei Cao[a], Weiyu Yu[a,b*] and Jiuchao Feng[a]

[a] *School of Electronic and Information Engineering, South China University of Technology, Guangzhou, China*

[b] *Provincial Key Laboratory for Computer Information Processing Technology, Soochow University, Suzhou, Jiangsu 215006, China.*

**Corresponding author*

Abstract

Image segmentation evaluation is still a hotspot problem. Various methods of image segmentation evaluation have been proposed. Amongst all the evaluation approaches, Segmentation Entropy Quantitative Assessment (SEQA) is one of the most popular methods. In this paper, segmentation entropy is proposed. In experiments, some standard images which are segmented by multi-level thresholds are tested and used to conclude the characteristics of SEQA, including its application conditions, advantages and disadvantages in image segmentation evaluation.

keywrods:SEQA, Segmentation Entropy, Multi-Threshold Segmentation

1. Introduction

Image segmentation is an important task in image processing. It is the prerequisite of image analysis and understanding. Dozens of criterions of image segmentation evaluation based on various indexes are proposed, such as probabilistic rand index [1], variation of information [2], global consistency error [3], and boundary displacement error [4]. Amongst all the evaluation approaches, segmentation entropy quantitative assessment (SEQA) is a popular method.

Entropy is a concept originating from information theory, first proposed by Shannon [5]. It calculates the amount of information in the message, which is consisted of a countable length of character

* Corresponding author. Tel.: +86-020-22236090; fax: +086-020-22232470
E-mail address: yuweiyu@scut.edu.cn

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combination. By computing the total probabilities of all the characters in the message, we obtain the information entropy of the message.

Learning from information theory, the term of entropy has also been introduced into the field of image processing to estimate the quantitative information of an image. Thus, the image entropy turns out to be the computation of pixel value probabilities.

Entropy is used to compare the variation of information of original image and segmented image. We obtain the information loss and gain directly so as to get the quality of the process, which actually estimates the effect of segmentation. The segmentation evaluation method based on entropy is called Segmentation Entropy Quantitative Assessment (SEQA).

The rest of this paper is arranged as follows. In Section II, SEQA algorithm is introduced. In Section III, we illustrated its application conditions, displayed the assessment performances of 2-D entropies and summarize the characteristics of SEQA. Finally, Section IV concluded the paper.

2. SEQA Algorithm

2.1. 1-D Image Segmentation Entropy

Consider a $m \times n$ image f with gray $\{x_1, x_2, .;.., x_k\}$. If the probability of each pixel value x_i in image f is $p(x_i)$. Then, the amount of information contained within each pixel can be represented as follows:

$$h(x_i) = -p(x_i) \times \log p(x_i) \tag{1}$$

The total amount of information in an image f will be obtained as follows:

$$H(f) = -\sum_{i=1}^{k} h(x_i) \tag{2}$$

Suppose that an image f is divided into s sub-regions $\{r_i\}_{i=1}^{s}$, thus the regional entropy of each sub-region $H(r_i)$ can be calculated from Eq. 2. We attain the image segmentation entropy H_{1D} [6]:

$$H_{1D} = \frac{\sum_{i=1}^{s} H(r_i) - H(f)}{H(f)} \tag{3}$$

Since the segmentation entropy is based only on the pixel value itself, it is also called 1-D image segmentation entropy. It represents the variation ratio of the entropy of segmented images comparing with the original image.

As shown in Fig.1, the value of $h(x_i)$ initially increases, but then decreases as the probability $p(x_i)$ ascends. The peak value which the $p(x_i)$ reaches is about 0.37. Generally, pixel value of an image ranges from 0 to 255, and most probabilities of these pixels are smaller than 0.2. Therefore, rarely could any single pixel information of an image exceed the ideal peak value. On this basis, we can conclude that, for most images, the larger H_{1D} is , the more information from the segmented images we can get. Thus, the better effect we can achieve.

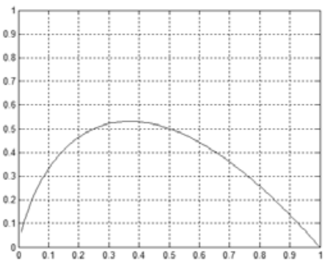


Figure.1 Mathematic Characteristics of $h(x_i)$

2.2. 2-D Image Segmentation Entropy

In natural and synthetize images, the distribution of pixel values appears more randomly, or shows strong correlation with its neighborhood pixels. In such cases, 1-D image segmentation entropy may be unable to provide correct evaluation. To address this problem, an improved approach was proposed, called 2-D image segmentation entropy.

2-D image segmentation entropy considers both the pixel value itself and the average value of its 8 neighborhood pixels [7], which consist of two parameters of the entropy $\left(x_i, y_j\right)$.

The probability of pixel value x_i and its 8 neighborhood pixel value y_j is p_{ij}. Thus, 2-D image entropy $H_{2D}(f)$ of the original image is:

$$H_{2D}(f) = -\sum_{i=1}^{L}\sum_{j=1}^{L} p_{ij} \times \log p_{ij} \tag{4}$$

An image f is divided into s sub- regions $\{r_i\}_{i=1}^{s}$, thus the 2-D region entropy of each sub-region $H_{2D}(r_i)$ can be calculated from Eq. 4.We can obtain the 2-D image segmentation entropy H_{2D} as following:

$$H_{2D} = \frac{\sum_{i=1}^{s} H_{2D}(r_i) - H_{2D}(f)}{H_{2D}(f)} \tag{5}$$

Similarly to the principle of 1-D image segmentation entropy, probabilities of most pixel values as well as its neighborhood value are small. Thus, for most images, if the H_{2D} is higher, more information will be got from these segmented images.

2.3. Application Condition

Like many assessment methods, SEQA has its own application conditions. Therefore, when image has only several pixel values or its pixel value distribution is extremely intense. For example, with respect to an image of a brain (see Fig.2 and Fig.3), the best segmentation should be judged by the smallest entropy, rather than the largest one as introduced in this paper.

3. Experimental results

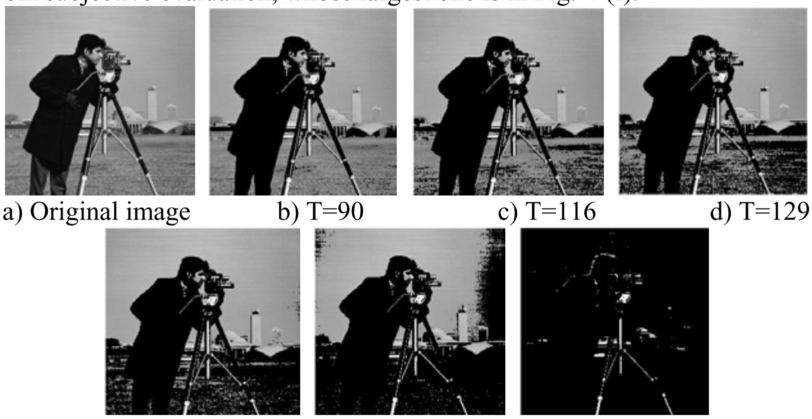
3.1. Single Threshold Segmentation Evaluation

In this section, we test some standard images with different thresholds. The original images, and the segmented foreground images are shown in Fig.2, 3 and 4. 1-D and 2-D segmentation entropies are shown in Table1.

We test “Cameraman” image and evaluate the performance of SEQA. In Fig2-b), only the detail of the pants of the cameraman is separated. Fig. 2-(c)-(e), the environment background is increasingly segmented. In Fig. 2-(f),(g), the images are so over segmented that some parts of the image are incomplete.

For “Lena” image, we can also easily observe that, the target areas of Fig. 3-(b),(c) are rarely separated from the original image whilst those of Fig. 3-(f),(g) are somewhat over segmented. The best segmented images should be Fig. 3-(d),(e). The values of H_{1D} and H_{2D} show matched results, with the largest values arrives at Fig. 3-d) and 3-e), respectively.

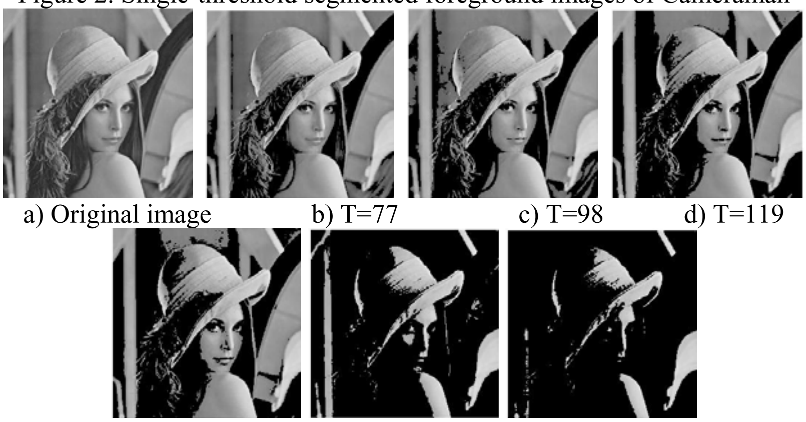
For "Pepper" image, it turns out to be a little hard to judge the segmentation result. Generally speaking, Fig. 4-(b) should be judged as failed segmentation as it leaves a large area of the background in the foreground part. In comparison, the foreground information of Fig. 4-(d)-(g) are over segmented to different extends. Among these segmented results, the best is Fig. 4-(c). The value of H_{2D} perfectly matches the result of subjective evaluation, reaching the largest value of 0.9504. But for H_{1D}, the value slightly differs from subjective evaluation, whose largest one is in Fig. 4-(f).



a) Original image b) T=90 c) T=116 d) T=129

e) T=142 f) T=157 g) T=192

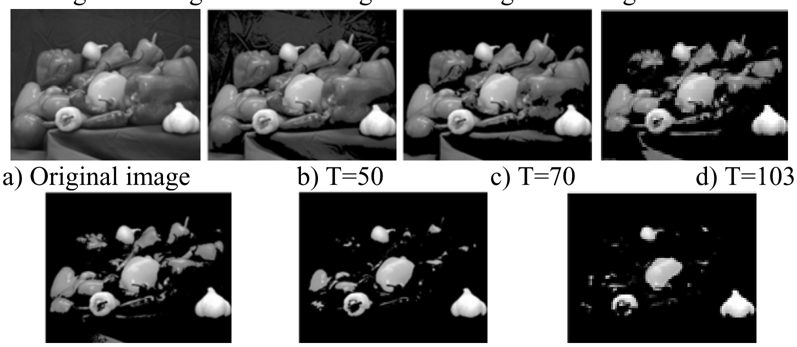
Figure 2. Single-threshold segmented foreground images of Cameraman



a) Original image b) T=77 c) T=98 d) T=119

e) T=126 f) T=165 g) T=180

Figure 3. Single-threshold segmented foreground images of Lena



a) Original image b) T=50 c) T=70 d) T=103

e) T=112 f) T=144 g) T=169

Figure 4. Single-threshold segmented foreground images of Pepper

TABLE1. SEQA of different single-threshold images

Cameraman			Lena			Pepper		
Threshold	H_{1D}	H_{2D}	Threshold	H_{1D}	H_{2D}	Threshold	H_{1D}	H_{2D}
90	0.6618	0.7004	77	0.6770	0.5428	50	0.5898	0.6181
116	0.7109	1.0662	98	0.7204	0.9265	70	0.7499	0.9504
129	0.7214	1.1503	119	0.7333	1.0506	103	0.8182	0.7579
142	0.7167	1.0936	126	0.7331	1.0725	112	0.8338	0.5738
157	0.6864	0.9705	165	0.7182	0.4238	144	0.8638	1.1467
192	0.7889	25.4515	180	0.6900	0.5408	169	0.8458	4.0689

3.2. Double-Threshold Segmentation Assessment

We test SEQA via three standard images with several double-thresholds. The original images listed in Fig.4-(a), Fig. 5-(a) and Fig. 6-(a) respectively. The segmented images are divided into three parts by two thresholds. Pixels of each region in the image of this part are given with single value. The double thresholds images are displayed in Fig. 5. Their 1-D and 2-D segmentation entropies are shown in Table2.

As displayed in the segmented images of Cameraman, Fig.7-b) separates the lawn best but the sky area and the dressing detail of the cameraman are not separated properly. Fig. 5-c) divided the lawn area into two regions, less superior to Fig. 5-a). The best threshold should respond to Fig. 5-a). The values of H_{1D} and H_{2D} show similar result with the largest values for Fig. 5-a). But others show different result .

Amongst the segmented images of Lena, Fig. 5-d) best separates the shadow, facial detail, hat decoration and the background of Lena, whilst Fig. 5-f) separates little shadow area of Lena., and Fig. 5-e) gives out the worst segmentation amongst three images. The value of H_{1D} and H_{2D} both reach peak value for Fig. 5-d),but their evaluations for the rest two are contrary. The H_{2D} value of Fig. 5-e) is the smallest amongst the three while H_{1D} value of Fig. 5-f) is the smallest.

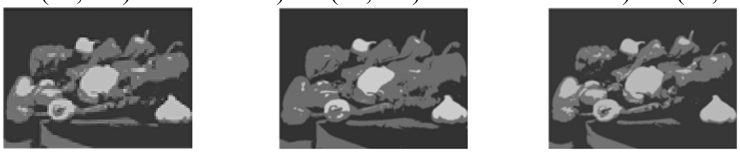
In terms of “Pepper” image, we observe that all three images separate the background perfectly. Amongst three images, Fig.7-g) and 7-i) separate the bottom part of lager objects better while Fig. 5-h) segregates the upper ones better. In short, the objects in Fig. 5-h) are separated most completely, but the results of the rest are quite similar to this one. Though the values of H_{1D} are quite similar to each other, they show different judgment, giving Fig. 5-h) the largest value. We can see that those values of H_{2D} have large disparity to each other, indicating the worst segmenting result displayed by Fig. 5-h).

TABLE2. SEQA of different double-threshold images

Cameraman			Lena			Pepper		
Threshold	H_{1D}	H_{2D}	Threshold	H_{1D}	H_{2D}	Threshold	H_{1D}	H_{2D}
70,142	1.3341	1.4113	91,149	1.3747	1.6587	82,150	1.5748	0.9657
56,157	1.2867	1.3672	77,180	1.3522	0.0053	70,169	1.5602	3.1988
90, 129	1.3203	1.0222	98,126	1.3079	1.4042	90, 144	1.5643	0.6491

a) T= (70,142) b) T= (56,157) c) T= (90,129)

d) T= (91,149) e) T= (77,180) f) T= (98,126)



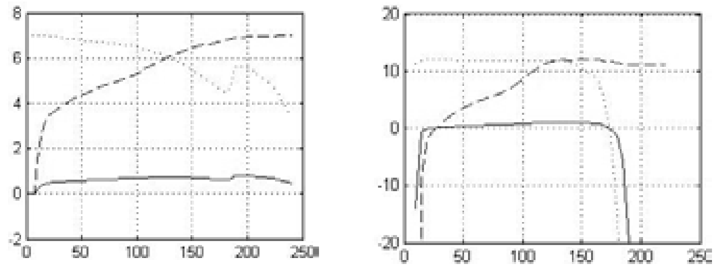
g) T= (82,150) h) T= (70,169) i) T= (90,144)

Figure5. Double-threshold segmented images

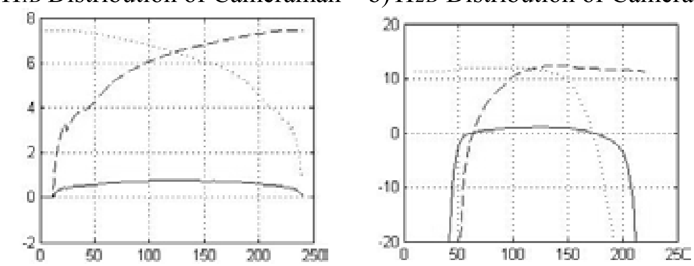
In accordance with above comparison, we can conclude that for single threshold segmentation, SEQA performs well in segmentation assessment, and the values of H_{1D} and H_{2D} match the subjective evaluation. However, in some cases, H_{1D} may result some evaluation errors, such as the H_{1D} value of Fig. 2-g) for Cameraman. Generally speaking, 2-D segmentation entropy performs more accurate and stable than 1-D segmentation entropy for single threshold segmentation.

Furthermore, if we segment the image by the order of pixel value covering the whole range and calculate every H_{1D} and H_{2D}. We can obtain the distribution curves of both segmentation entropies as Fig.4. It is worth noting that H_{1D} and H_{2D} represent the net increase of information amount between segmented areas and the original image. When the value of H_{1D} and H_{2D} are positive, they indicate that the total information amount of segmented areas is larger than that of the original image, so the segmentation is successful. Similarly, negative values indicate the loss of information quantities. From Fig.6, we can see that the value range of H_{2D} is far wider than that of H_{1D}. Any dissatisfaction of segmentation is shown much distinctly by H_{2D}.

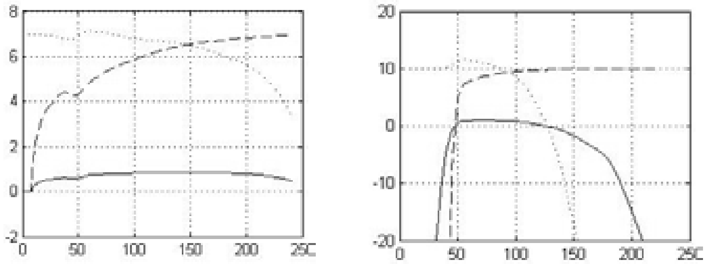
For multi-threshold segmentation evaluation, SEQA seems to appear some different results to subjective evaluation, especially for the 2-D segmentation entropy. This may attribute to information decentralization due to increased number of sub-regions.



a) H_{1D} Distribution of Cameraman b) H_{2D} Distribution of Cameraman



c) H_{1D} Distribution of Lena d) H_{2D} Distribution of Lena



e) H_{1D} Distribution of Pepper f) H_{2D} Distribution of Pepper

Figure 6. H_{1D} and H_{2D} distribution of three testing images

4. Conclusion

In this paper, we propose a novel entropy evaluation approach based on entropy for image segmentation. By showing the mathematics characteristics of segmentation entropy quantitative assessment, we conclude their application condition and evaluation criteria. We tested some standard images using several multiple level thresholds. Experiment results showed 2-D entropy assessment is more stable and accurate while 1-D entropy is more preferable in multiple-threshold segmentation assessment.

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